Performance Metrics for Image Contrast

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***Abstract*—In this paper, contrast level of the images are quantified by the two proposed metrics. These metrics are Histogram Flatness Measure (HFM) and Histogram Spread (HS). Computation of these metrics are based on the shape of the histogram. Extensive simulation results reveal that HS is more meaningful than HFM. Low contrast images have low HS value, while high contrast images have higher value of HS. Thus HS metric can be used to distinguish between the images having different contrast level. Accuracy of the metric is also verified for natural and medical images. This metric has broad applications in image retrieval, image database management, visualization, rendering and image classification.**

***Keywords*—Histogram, image contrast, image enhancement, histogram equalization.**

I. Introduction

Light creates shadows, emphasizes textures, moods and emotions in an image. Bad light is a cause of unnatural and poor image. When an image looks too dark, details are lost in the shadows. The image is called as underexposed. Overexposed image looks burned out, and details are lost due to saturation of pixels [1]. Contrast represents the quality of the image. Contrast has a great influence on the quality of an image in human visual perception as well as in image analysis. A poorly illuminated environment significantly affects the contrast and produces an unnatural image. Contrast can have a significant visual impact on an image by emphasizing texture. Histogram provides the information about the contrast of the image. However, the histogram of the aesthetically pleasing image could be very different from one another, while all of them may be rated as good contrast image by human observers. It is known that the shape of histogram can indicate the global characteristics of the image: dark, bright, low contrast, and high contrast [2]. Narrow histograms reflect less contrast and may appear dull or washed out gray, whereas broad histograms reflect a scene with significant contrast. It is logical that an image, whose pixels occupy the entire range of gray levels, tend to be distributed uniformly, will have high contrast and exhibit a large variety of gray tones. The net effect is that image will show a great deal of gray level details. In image processing, various algorithms (e.g. fog removal [3], [4], tone mapping [5] etc) produce the low contrast image output. These algorithms require post processing for the contrast enhancement. Contrast enhancement increases the total contrast of an image by making light colors lighter and dark colors darker at the same time. There can be number of choices for the post processing like histogram equalization, histogram specification, and histogram stretching [1], [2]. But the main problem is to ascertain to that whether the contrast enhancement is needed for the images or not. If an image has a good contrast then there is no use of contrast enhancement. Contrast enhancement of a good image may leads to an unnatural (overexposed or saturated) image. Thus we need a metric which can effectively quantify the contrast and thereby discriminate the good and poor contrast images.

II. Proposed metrics

In this article two performance metrics which quantify the spread and flatness of the image histogram are proposed. These metrics help us to distinguish between the low and high contrast images. Once we have effective performance metric for contrast, it will be possible to determine whether there is a need of contrast enhancement or not.

A. Histogram flatness measure (HFM)

Histogram flatness measure for the histogram ($h(x)$) is defined as

$$HFM = \frac{\exp[\int_{-\frac{1}{2}}^{\frac{1}{2}} \ln h(x)]}{\int_{-\frac{1}{2}}^{\frac{1}{2}} \ln h(x)} \tag{1}$$

where HFM is the ratio of the geometric mean of $h(x)$ to the arithmetic mean of $h(x)$. This is inline with the spectral flatness measure [6]. For a digital image, flatness of the histogram can be defined as

$$\begin{aligned} HFM &= \frac{\text{geometric mean of histogram count}}{\text{arithmetic mean of histogram count}} \\ &= \frac{(\Pi_{i=1}^{n} x_i)^{\frac{1}{n}}}{\frac{1}{n}\Sigma_{i=1}^{n} x_i} \end{aligned} \tag{2}$$

where x_i is the histogram count for the i^{th} histogram bin and n is the total number of histogram bins. HFM is the ratio of the geometric mean to the arithmetic mean of the histogram intensities. It is known that geometric mean of a data set is always less than or equal to the arithmetic mean, thus HFM ϵ [0,1]. It can be verified that the low contrast images (i.e. narrow and peaky histogram) have low value of HFM in comparison with the high contrast images (i.e. broad and

TABLE I: Histogram Flatness Measure (HFM) for test images for different contrast condition.

Image	Original	Low contrast (dark)	Low contrast (bright)	High contrast (histogram equalized)
'baboon'	0.5304	0.4941	0.4446	0.8152
'lenna'	0.6769	0.4236	0.6977	0.8816
'peppers'	0.6073	0.3885	0.6076	0.8609

TABLE II: Histogram Spread (HS) for test images for different contrast condition.

Image	Original	Low contrast (dark)	Low contrast (bright)	High contrast (histogram equalized)
'baboon'	0.2314	0.1529	0.1765	0.4196
'lenna'	0.2941	0.2275	0.2235	0.4275
'peppers'	0.3137	0.2627	0.2549	0.4392

flat histogram). It is noted that for the calculation of geometric mean and arithmetic mean, bins having zero count are ignored.

B. Histogram Spread (HS)

Histogram Spread (HS) can be defined as

$$\begin{aligned} HS &= \frac{\text{Quartile distance of histogram}}{\text{Possible range of pixel values}} \\ &= \frac{(3^{rd}\text{quartile} - 1^{st}\text{quartile})\text{of histogram}}{\text{(maximum-minimum) of the pixel value range}} \end{aligned} \quad (3)$$

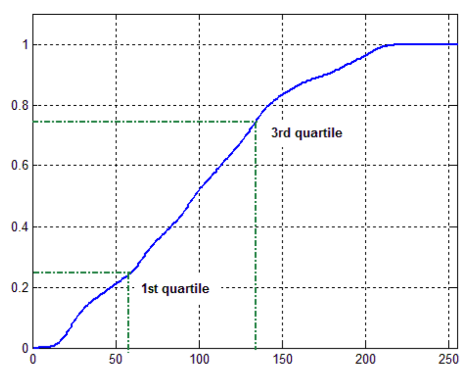

Fig. 1: Cumulative histogram of the 'lenna' image. Positions of the 1^{st} and 3^{rd} quartile are marked.

Histogram spread is the ratio of the quartile distance to the range of the histogram. Quartile distance is denoted as the difference between the 3^{rd} quartile and the 1^{st} quartile. Here 3^{rd} quartile and 1^{st} quartile means the histogram bins at which cumulative histogram [2] have 75% and 25% of the maximum value respectively (see Fig.1). Range is the difference between the possible maximum & minimum intensities of the image (i.e. for 8 bit image minimum & maximum intensities are 0 and 255 respectively). Thus for the image having uniform distribution, the value HS is 0.5, while for binary image (0 and 255 only) the value of HS is 1. Hence for all normal gray scale images having unimodal histogram, the value of the measure may less than 0.5, while for the images having multimodal histogram, HS ϵ (0,1]. It can be verified that the low contrast images (i.e. narrow and peaky histogram) have low value of HS in comparison with the high contrast images (i.e. broad and flat histogram) [2].

III. Simulation and Results

TABLE III: Histogram Spread (HS) for natural and medical images for different contrast condition.

Image	Low contrast	High contrast
'lonavala'	0.0549	0.3882
'gangasagar'	0.1490	0.3294
'lung CT'	0.2667	0.6392
'mammogram'	0.2078	0.5373

Metrics are computed for various well-known 8-bit gray scale images: 'baboon', 'lenna', and 'peppers'. Simulation is performed in MATLAB 7.0.4 environment. High contrast (contrast enhanced) and low contrast (dark & bright) version of the image are generated by linearly stretching/squeezing the histogram of the image. Quantitative analysis for the HFM is shown in Table I. Results show that low contrast dark images have HFM value less than the original images. While some cases of low contrast bright images have HFM value greater than the original images, which contradict the notion of contrast. The anomaly of the result is attributed to the digitalization of gray scale and the approximation used to calculate the HFM. Quantitative analysis for the HS is shown in Table II. Results show that high contrast images have more value of the histogram spread (HS) in comparison with the low contrast (dark & bright) images. This performance metric complies with the general notion of contrast that spread of histogram can effectively distinguish the different contrast conditions of the images. Unlike the HFM, HS depends not only on the intensity values of the histogram but also on the histogram bin positions, thus giving accurate results. Fig.2 clearly shows that low and high contrast images have a different histogram width and can be discriminated by the HS. Simulation is also performed over natural and medical images: 'lonavala', 'gangasagar', 'lung CT', and 'mammogram' (see

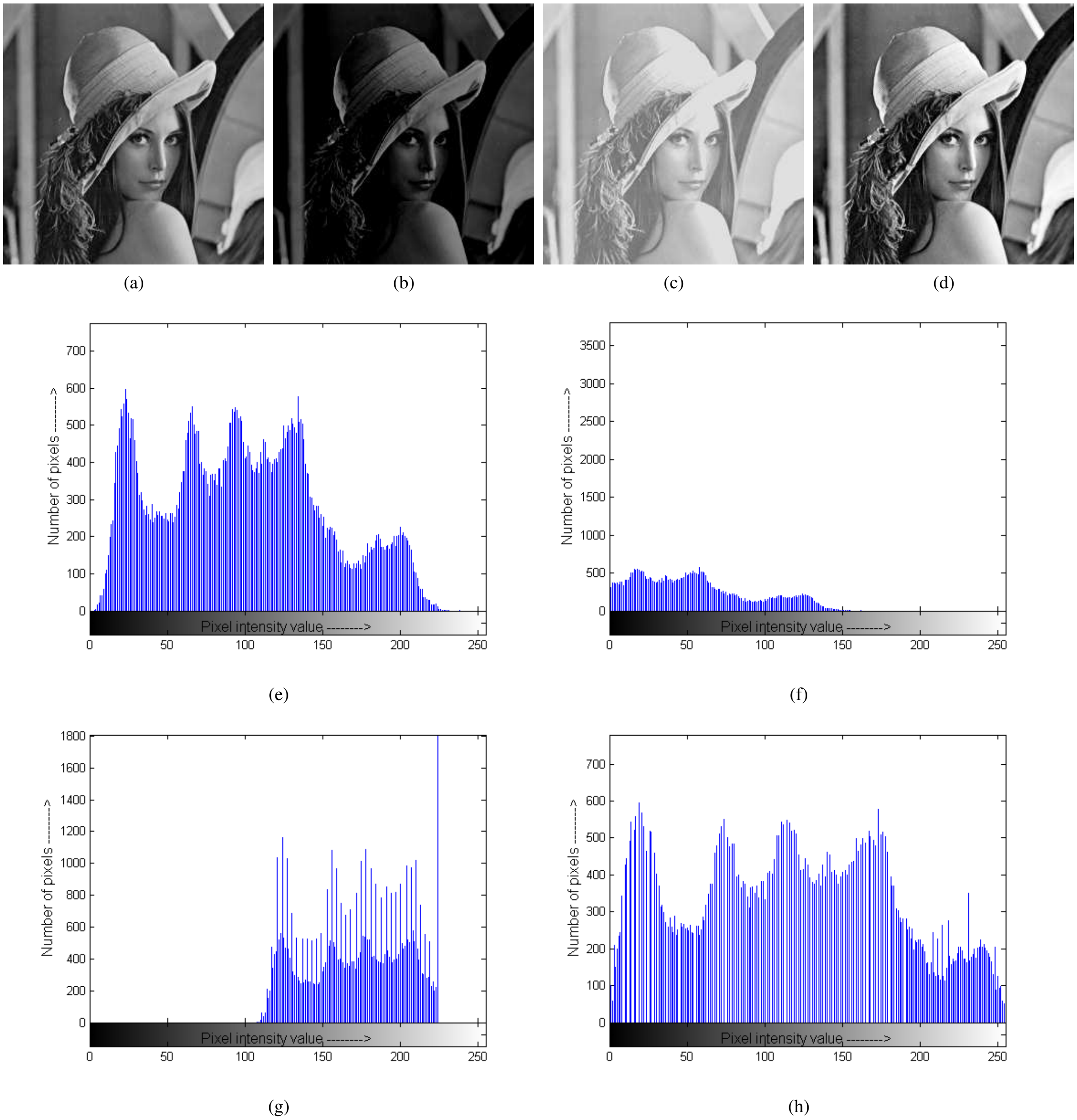

Fig. 2: (a)Original ‘lenna’ image, (b) low contrast(dark) ‘lenna’ image, (c) low contrast (bright) ‘lenna’ image, (d) histogram equalized ‘lenna’ image, Histogram of (e)Original ‘lenna’ image, (f) low contrast(dark) ‘lenna’ image, (g) low contrast (bright) ‘lenna’ image, (h) histogram equalized ‘lenna’ image.

Fig.3). Values of HS for these images are shown in Table III. These results verify the efficacy of the proposed metric HS.

IV. Conclusion

In this paper, two performance metrics (HFM & HS) for the measurement of contrast in the images are proposed. Simulation results with popular images, natural images, and medical reveal that out of the two proposed metrics HS is more meaningful than HFM. The reason is that HS consider the histogram counts as well as histogram bin locations. HS can effectively discriminate low & high contrast images. Once the quantitative value for the contrast of the image is known, it is easier to say whether there is a requirement of contrast enhancement or not. Thus we can trade off between the computation and a more pleasing image output.

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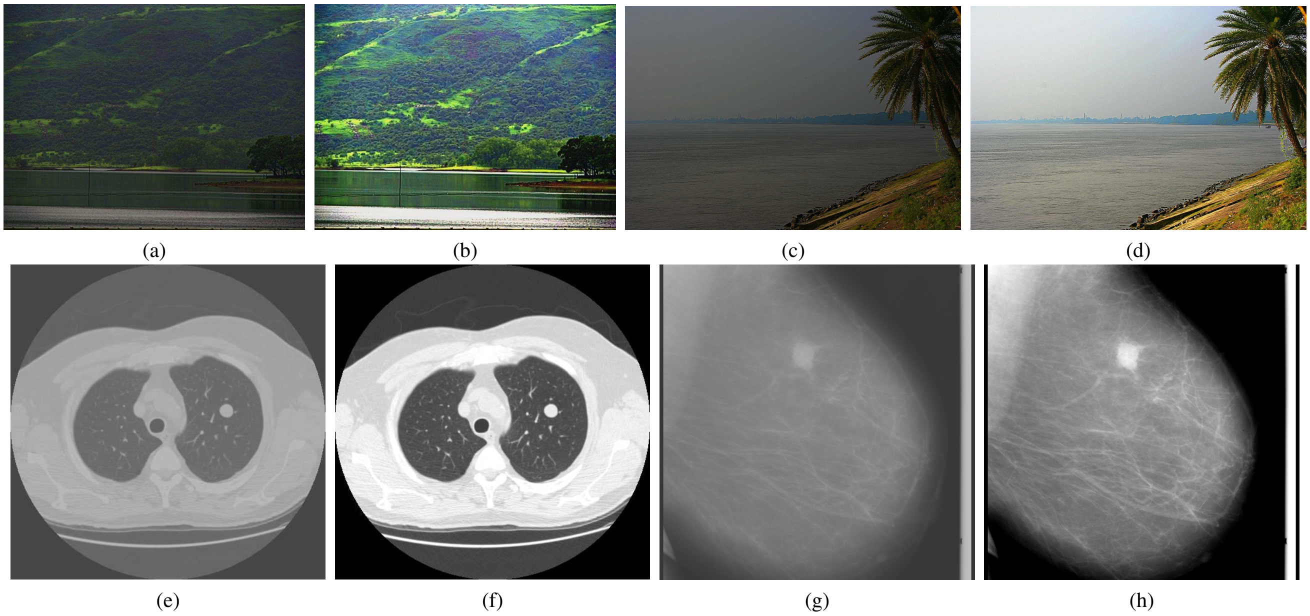

Fig. 3: (a) Low contrast 'lonavala' image, (b) high contrast 'lonavala' image, (c) low contrast 'gangasagar' image, (d) high contrast 'gangasagar' image, (e) low contrast 'lung CT' image, (f) high contrast 'lung CT' image, (g) low contrast 'mammogram' image, and (h) high contrast 'mammogram' image.

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